After rain comes sunshine

Forecasting Solar Irradiance in Los Angeles

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General Assembly

DSIR-0320 Project 4

Problem Statement

Grid integration of renewable energy

Task: Forecast **Global Horizontal Irradiance** 1-4 days into the future, in LA county

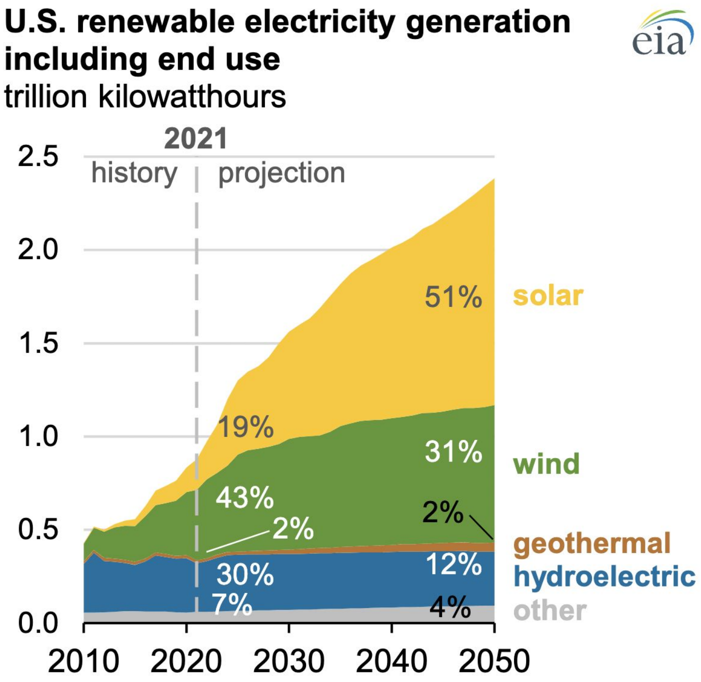
National Solar Radiation Database

Evaluate success with:

1) root mean squared error (RMSE)
2) mean absolute error (MAE)

For **daylight** predictions

Compare against baseline model of an **average day**



Source:
https://www.eia.gov/todayinenergy/detail.php?id=51698

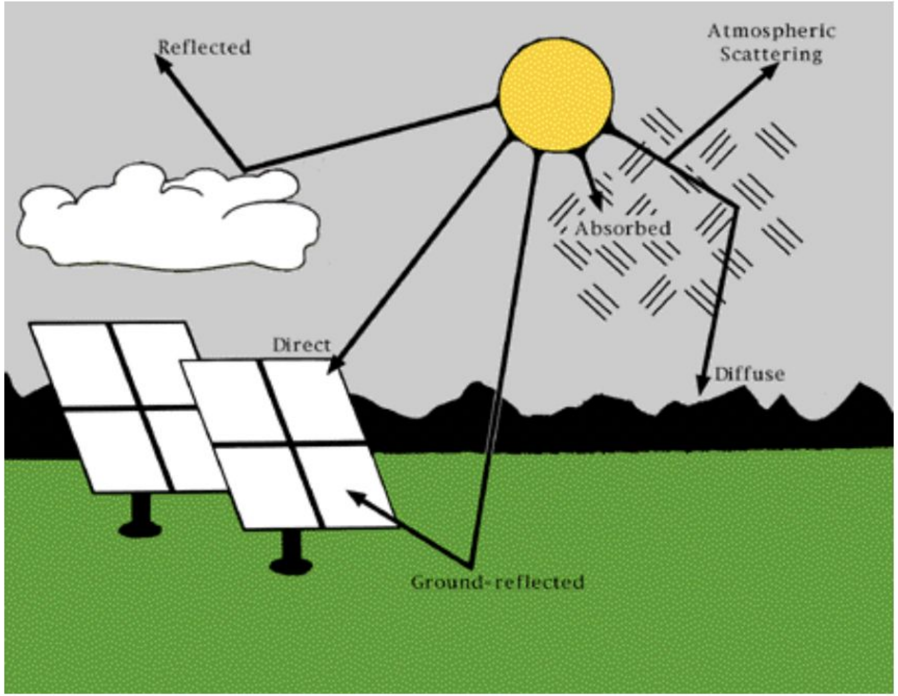
What is Global Horizontal Irradiance?

Radiation on a horizontal surface

Sum of all rays hitting a detector

GHI correlates the best with sun received by photovoltaic systems

Units W/m^2



Source; https://www.homerenergy.com/products/pro/docs/3.11/global_horizontal_irradiance_ghi.html

National Solar Radiation Database (NSRDB)

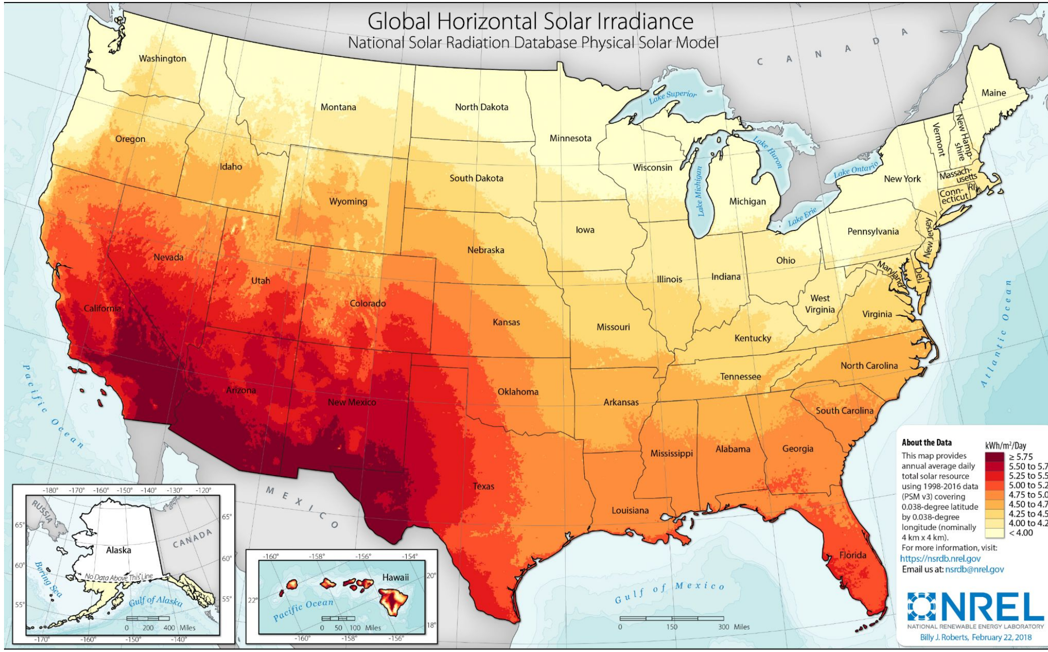
Publicly accessible

Weather data (from satellites)

2x2 km resolution, 30 min timesteps

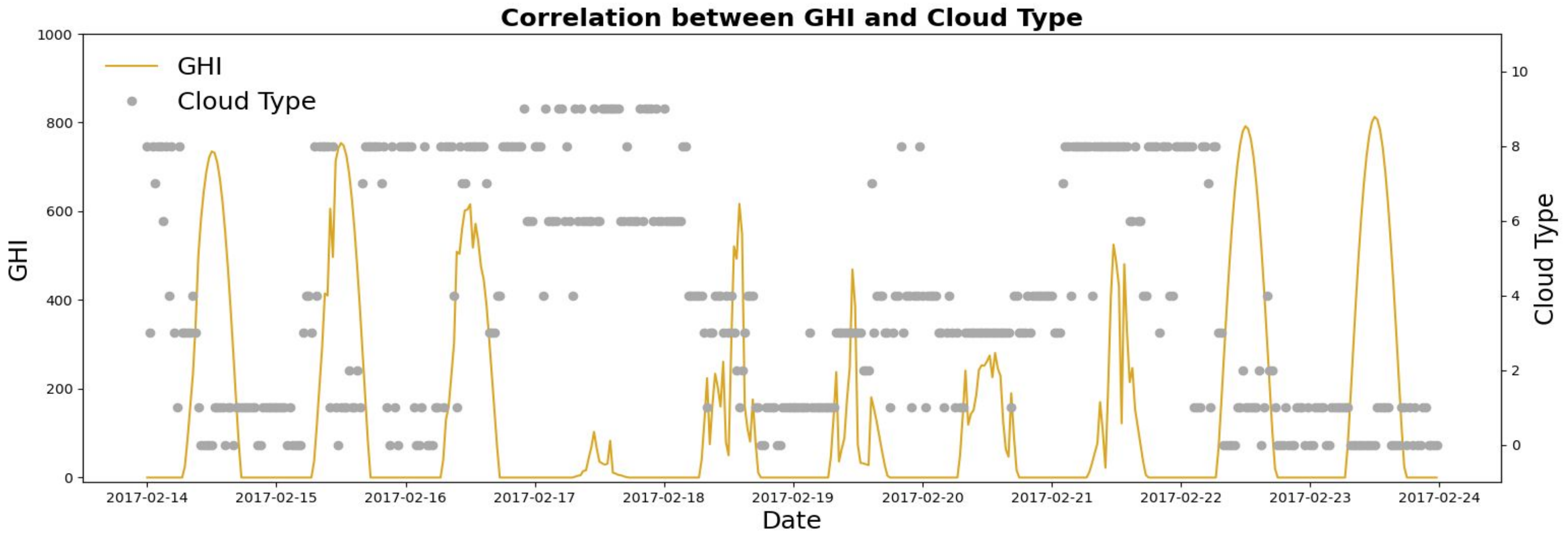
Model of GHI

Collected data from 2016-2020, using the NSRDB API



Source:
https://www.nrel.gov/gis/solar-resource-maps.html

Exploratory Data Analysis



No data cleaning required (!)

Cloud types cause a lot of short-term variation

Two types of seasonal variation: **daily** and **yearly**

Model features

We feature engineered:

- *Day Seasonality* and *Yearly Seasonality* with trigonometric functions
- Wind Speed and direction -> Wind x and y components

Additionally, we used features with high correlation to GHI:

- *Wind_x*, *Wind_y*, *Pressure*, *Relative Humidity*, *Dew Point*, *Temperature* and *Solar Zenith Angle*
- *Cloud Type* as a categorical feature

Modeling Approach

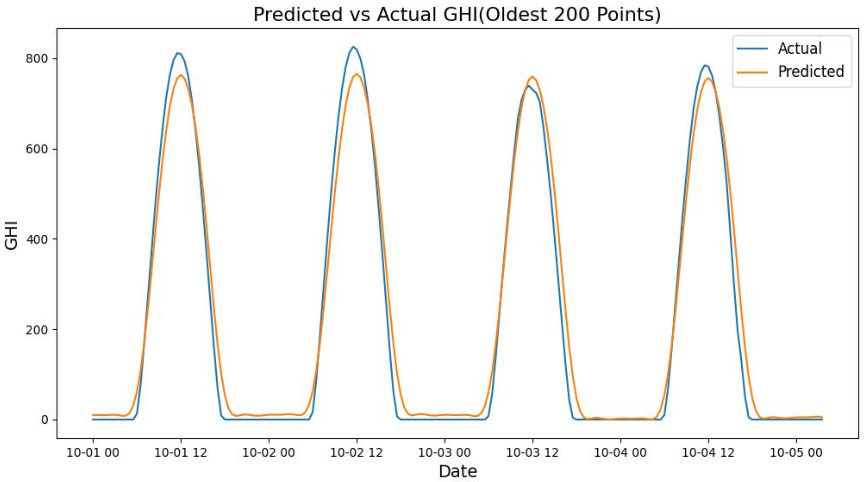
‘Traditional’ time series models require assumptions (eg stationarity)

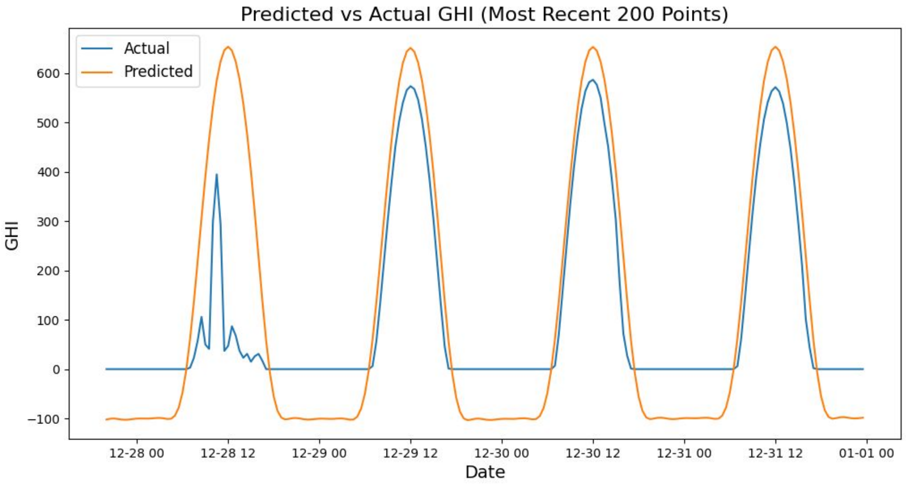
- Difficult to forecast many timesteps in advance

We used three alternative models:

- **Neural Prophet**: uses lagged values of GHI to forecast future values of GHI
- **Recurrent Neural Network**: uses meteorological features
- **WaveNet**: uses meteorological features

Neural Prophet

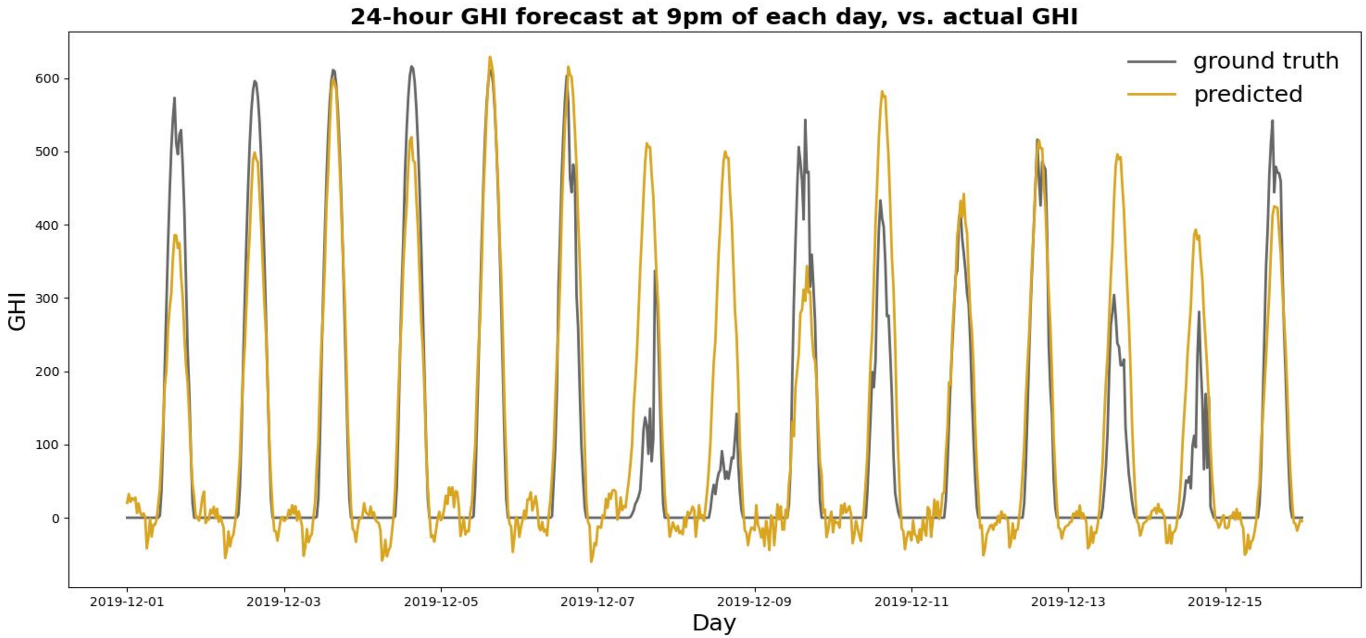




- Actual vs. predicted for 200 timesteps(4 days, 3 hours) in October 2020

- Actual vs. predicted for 200 timesteps(4 days, 3 hours) In December 2020

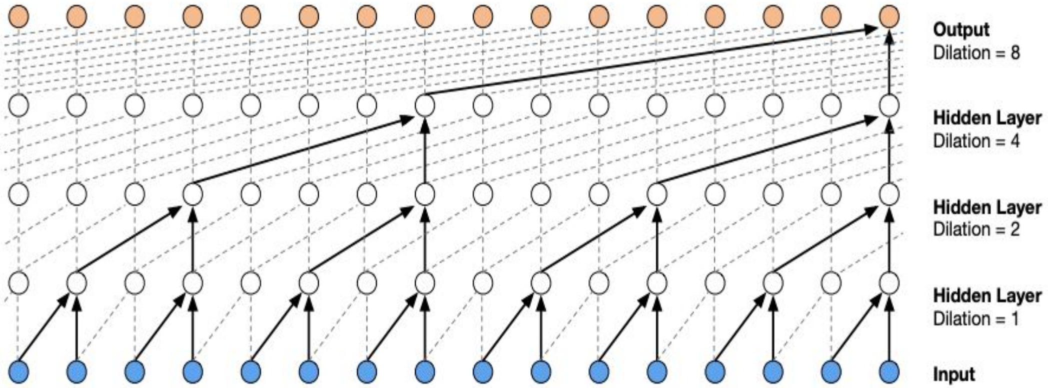
Recurrent Neural Network



Simple topology: 2 ‘Long short-term memory’ layers, one dense output layer

Use weather from 4 days to forecast 1 day ahead

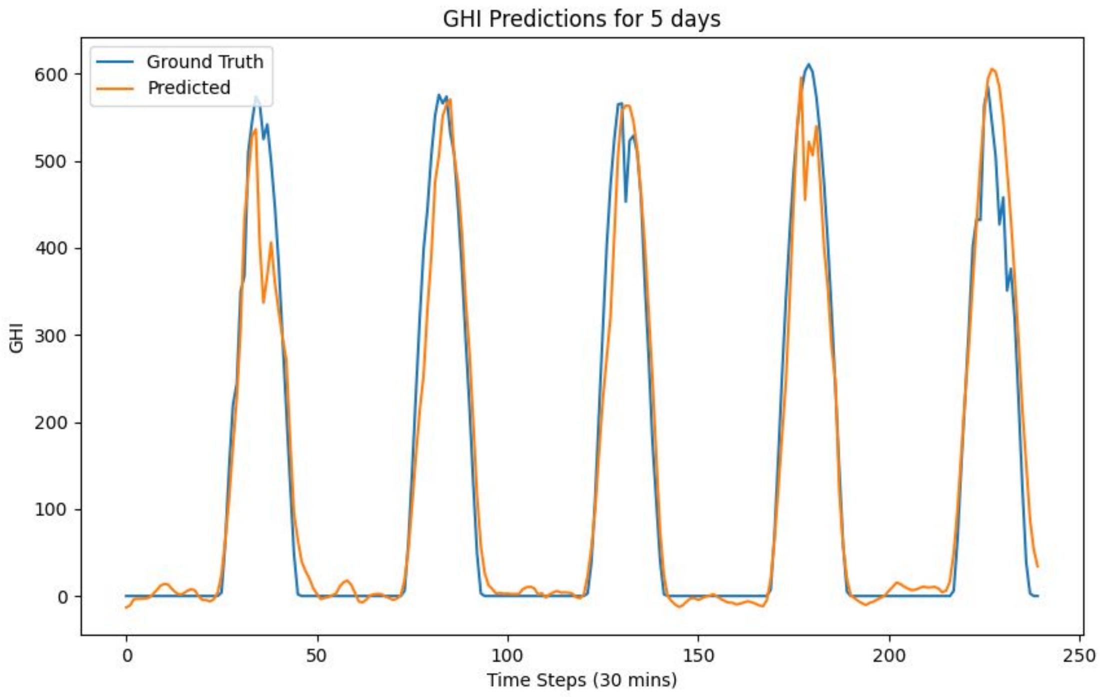
WaveNet Model



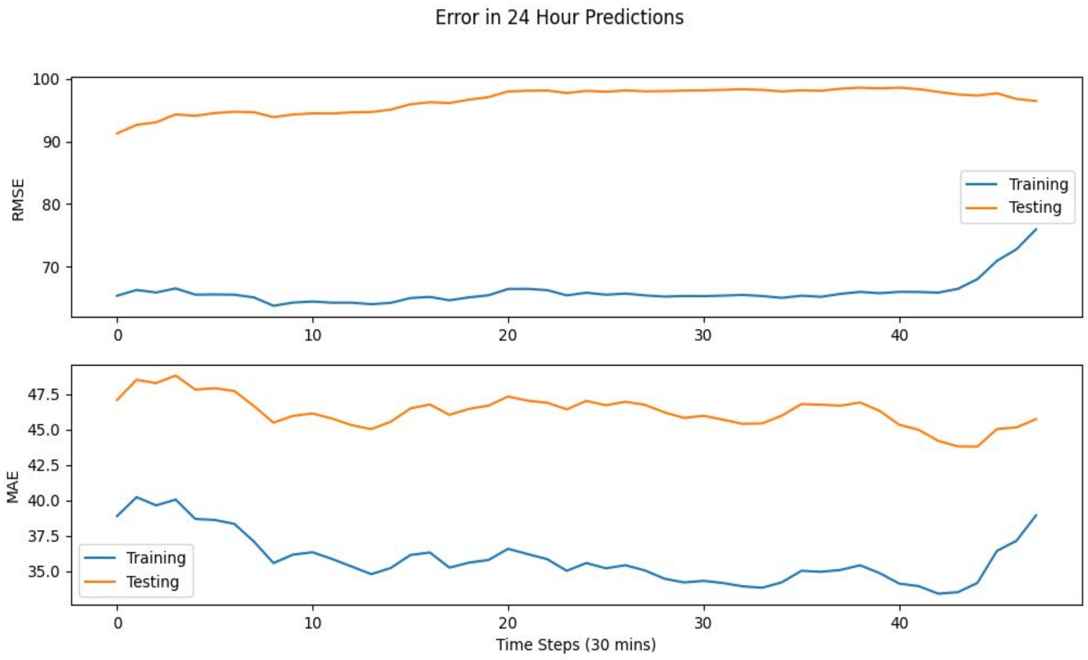
- Main features:
  - Stacked *Dilated* Convolutional Layer Blocks.
  - Good for large sequencing (multi-time step)
- Originally for univariate time signals
- Modified for larger dimensions

WaveNet Model

- Pros:
  - Identifies peaks
  - Minimal noise from nighttime
- Cons:
  - Inaccurate shape
  - Overcompensates deviations



WaveNet Model

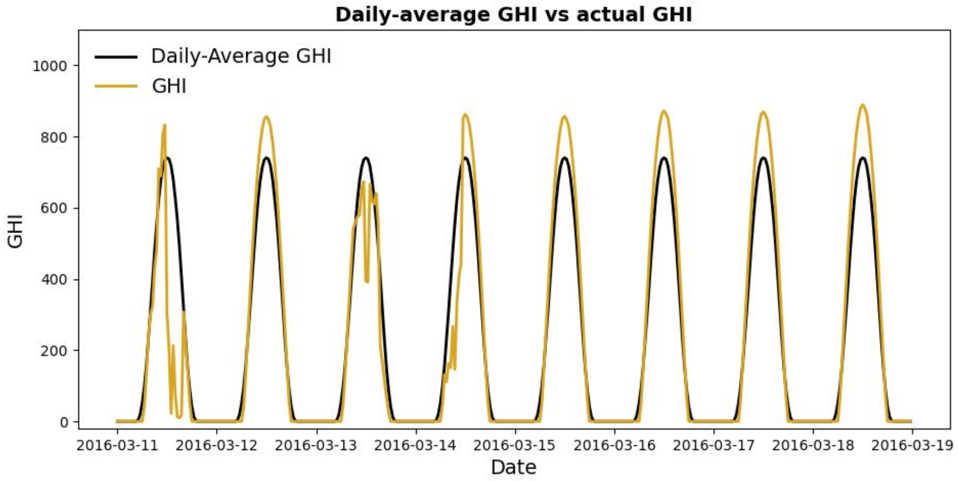


- Consistent errors over 24 hours
- Overfitting on Training set

Model Scores

Average day as Baseline Model

Only score for timestamps where the sun is up



Model	Training RMSE	Testing RMSE	Training MAE	Testing MAE
Baseline	N/A	198.4	N/A	160.7
Neural Prophet	120.48	101.96	87.82	59.25
RNN	106.5	119.9	72.1	78.0
WaveNet	91.4	135.0	59.6	81.54

Conclusions and Recommendations

- **Neural Prophet** performs best on the test data, but requires GHI
- For weather data inputs, the **RNN** performs best
- Clouds can make forecasts difficult!
- Next steps: probabilistic forecasting


Q
A

Sources

- NREL API Key
- Global Horizontal Irradiance Overview
- NSRDB: National Solar Radiation Database
- Neural Prophet: Explainable Forecasting at Scale
- NeuralProphet: A Neural Network based Time-Series Model
- Recurrent Neural Networks(RNNs) and LSTMs for Time Series Forecasting
- WaveNet: A Generative Model for Raw Audio
- Conditional Time Series Forecasting with Convolutional Neural Networks